THE EFFECT OF VEGETATION PRODUCTIVITY ON MILLET PRICES IN THE INFORMAL MARKETS OF MALI, BURKINA FASO AND NIGER

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Abstract. Systematic evaluation of food security throughout the Sahel has been attempted for nearly two decades. Food security analyses have used both food prices to determine the ability of the population to access food, and satellite-derived vegetation indices that measure vegetation production to establish how much food is available each year. The relationship between these two food security indicators is explored here using correspondence analysis and through the use of Markov chain models. Two sources of quantitative data were used: 8 km normalized difference vegetation index (NDVI) data from the Advanced Very High Resolution Radiometers (AVHRR) carried on the NOAA series of satellites, and monthly millet prices from 445 markets in Mali, Niger and Burkina Faso. The results show that the growing season vegetation production is related to the price of millet at the annual and the seasonal time scales. If the growing season was characterized by erratic, sparse rainfall, it resulted in higher prices, and well-distributed, abundant rainfall resulted in lower prices. The correspondence between vegetation production and millet prices is used to produce maps of millet prices for West Africa.

1. Introduction

Systematic evaluation of food security throughout the Sahel has been undertaken for nearly two decades. Organizations devoted to famine early warning use many types of data to identify communities that are potentially food insecure. These data include satellite-derived vegetation indices, public health surveys, participatory rural appraisals as well as current market prices of staple foods. A subjective "convergence of evidence" The skill of prediction has important implications for improving the food security and development policies in the region. Here we test the hypothesis that spatial food price predictions can be improved using formal analyses of vegetation production and market prices.

In the Sahel and Sudanian regions of Mali, Niger and Burkina Faso, over 85% of the population grows food in subsistence rain-fed agricultural systems as all or part of their income generating activities (Galvin and Ellis, 1997). Nevertheless, access to food for these farmers also involves markets where grain is bought and sold. Food security is therefore influenced both by local production and by the price

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and availability of food produced elsewhere. Establishing a relationship between vegetation conditions in the local area and the price of food in the market may allow improved detection and forecasts of food insecurity.

The majority of rural agriculturalists in Mali, Burkina Faso and Niger have a flexible response to food supply and demand. Farmers typically sell a portion of their crop on the market after harvest, save a portion for consumption, and purchase food from the market as their own supplies diminish later in the year. This interaction with the market tends to amplify the response of market prices to the production of low-cost, locally grown grains such as millet. The farmer's flexibility in timing the sale of grain provides a linkage between grain prices in the spring and summer and the vegetation conditions during the previous summer's growing season. Because climate change in West Africa may cause increasing variability in rainfall from year to year, how subsistence farmers can adapt to increasing variability in production as well as prices has implications for future food security of the region.

Higher prices can cause food insecurity among the most vulnerable in a population even in times with adequate or even abundant food supplies (Sen, 1981). Early warning of these price increases can enable organizations to increase food or income assistance in order to reduce the loss of lives and livelihoods as well as the cost of providing these services (FEWS, 2000). Early warning of impending food insecurity has become the focus of numerous organizations world wide, and new tools and methodologies to improve early detection of price increases is an important goal.

Monthly averages of normalized difference vegetation index (NDVI) from a 40 $\times$ 40 km area around each market is used to estimate variations in millet yields from year to year. This is possible because the growth and maturation of millet occurs with surrounding vegetation, enabling the vegetation production signal detected by NDVI to estimate variations in millet production (Fuller, 1998). NDVI is used by famine early warning systems, in conjunction with other indicators, to estimate the overall health of crops throughout Africa (Maselli et al., 1993; Fischer, 1994; Reynolds et al., 2000).

The objective of this research was to examine the relationship between satellite measurements of vegetation production and millet prices in Burkina Faso, Mali and Niger using models based on Markov chains of current and future market price of millet. Markov process can be defined as one in which the probability of being in a given state (a commodity price) at some particular time can be obtained from a knowledge of the immediately preceeding state. The models used here were based on the assumption that prices follow a Markov process, in that previous prices influence, but do not rigidly control, subsequent prices (Samuelson, 1971).

2. Methodology

We investigated how price (P) levels can change depending on the vegetation production during different months and different years.

TABLE I
Example probability state-transition matrix for prices

i/j	1	2	...	T
1	n_{11}	n_{12}	...	n_{1T}
2	n_{21}	n_{22}	...	n_{2T}
:	:	:	:	:
T	n_{T1}	n_{T2}	...	n_{TT}

2.1. CORRESPONDENCE ANALYSIS

The temporal characteristics of prices were explored using a correspondence analysis between price variability and the time of year. Correspondence analysis is a technique for displaying associations among a set of categorical variables in a scatterplot or map, that allows a visual display of the patterns within the data (Everitt and Dunn, 2001). The analysis indicates whether certain levels of one trait are associated with some levels of another. The observed association of the two traits is summarized by conducting a geometric analysis on the resulting two-way contingency table. Our implementation of correspondence analysis is based on the singular value decomposition of the matrix whose elements are based on the chi-squared statistic. Details of this implementation can be found in Everitt and Dunn (2001).

2.2. MARKOV AND PRICES

Because we were interested only in large changes of the price and not in predicting the price exactly, the millet prices were quantized into T groups of 22 CFA/kg (the CFA Franc is the currency used throughout the study region). The number of times (n_{ij}) the price went from group T_i to group T_j was counted and placed in a contingency table $T \times T$ (Table I).

A probability state-transition matrix ‘P’ with elements P_{ij} ($i, j = 1,2,\ldots T$) was calculated from this table by dividing each n_{ij} by the tsum of the row ie $P_{ij} = n_{ij}/n_i$, where $n_i = \sum_{j=1}^{T} n_{ij}$ (Bailey, 1964). A χ^2 test was performed on the Markov matrix created from all available data to determine whether the process is a first order Markov.

A property of the Markov process is that if the initial price is multiplied by the probability matrix multiple times, the matrix will converge to the same probabilities for every starting price.

$$\lim_{n\to\infty} p^{(n)} = \lim_{n\to\infty} P^n p^o = p_o$$

Because of the continuity of the matrix P, p_o is an eigenvector of the matrix P with eigenvalue 1:

$$P_{p_o} = p_o$$

This eigenvector was used to characterize the Markov chain.

The Markov models were evaluated using quantized predictions of the price from the transition matrices. To determine the goodness-of-fit of the model, predicted prices were compared with the actual quantized prices and the root mean square error (RMSE) and the relative error were computed (D'Agostino, 1986).

The information about vegetation production was used to modify these markov models in order to determine how variations in production affect prices. First, the anomaly for the normalized difference vegetation index (NDVI) from June to September was computed by subtracting the mean for the period over the entire record, providing a measure of the vegetation production for each year in relation to the mean. This anomaly was then used to determine the input into the Markov matrices: the prices from years with different levels of vegetation production were used to create the probability tables, which were used to improve the price estimations and the RMSE measured from one to twelve months in advance. New Markov probability matrices based on the millet prices from years with different production anomalies were created. Millet prices were predicted 12, 4 and 1 month in advance by multiplying the starting price by the probability matrix according to the vegetation production anomaly.

The matrices created by counting the number of times the NDVI was in one of ten ranges of 50 NDVI units during each month had ten rows (quantized levels of vegetation density or NDVI groups) and 12 columns (months).

3. Data

Monthly millet prices from 445 markets in Niger, Mali and Burkina Faso (Figure 1) were used. The data were obtained from local market price monitoring organizations by the Famine Early Warning System (FEWS) (May, 1991; Chopak, 1999). Prices were kept in the local currency (CFA), which was fixed to the French Franc at the same exchange rate for all three countries during this study. The data series vary in length but have similar means and standard deviations (Figure 2, top panel). Across the three countries, 34,425 data points from 445 markets were used. The data for each country were deflated with a national, annual consumer price index (CPI) (IMF, 1999) interpolated across months. Although local variations in price trends may not be captured fully because the CPI was calculated in the capital city.

Although there were fewer markets with prices in the early 1980s than in the late 1980s and 1990s (from approximately 50 markets to 275 markets for each time period), no discontinuity or bias was seen in the dataset as a result of this change,

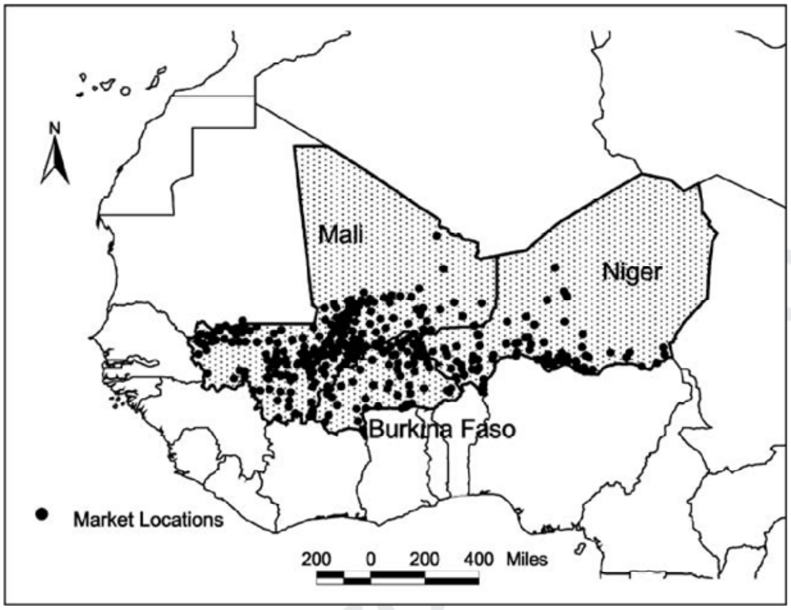


Figure 1. Map of the locations of the 445 markets with millet prices in Mali, Burkina Faso and Niger. Prices were collected by the Famine Early Warning System, www.fews.net.

and the variability introduced by sampling differences was less than the uncertainty of the price data.

Vegetation productivity was measured using NDVI data calculated from land surfaces radiances measured by the NOAA Advanced Very High Resolution Radiometer (AVHRR) at 8×8 km spatial, and monthly time resolution (Tucker, 1979). The data used for this study were from the archive processed by the Global Inventory Monitoring and Mapping Study (GIMMS) group at the NASA Goddard Space Flight Center (Brown et al., 2004; Pinzon et al., 2005; Tucker et al., 2005). The AVHRR sensor has appropriate spatial, spectral and temporal resolutions for monitoring the vegetation of the large geographic area of West Africa (Townshend, 1994) (Figure 2, bottom panel). The mean of 25 pixels in a five by five-pixel box (40×40 km) centered on each market was calculated from monthly maximum value composites (Tucker, 1985). Here we use the NDVI values, which are between 0 and 1, multiplied by 1000 to reduce rounding errors.

NDVI has been used extensively in the Sahel to detect variations in vegetation production, and has been shown by a number of authors to be correlated to both net primary production and crop yields (Tucker, 1985; Prince, 1991; Tucker et al., 1991; Fuller, 1998), and precipitation (Tucker and Nicholson, 1999). An anomaly time series based on the growing season months of July to September was used to determine the overall seasonal conditions in the region.

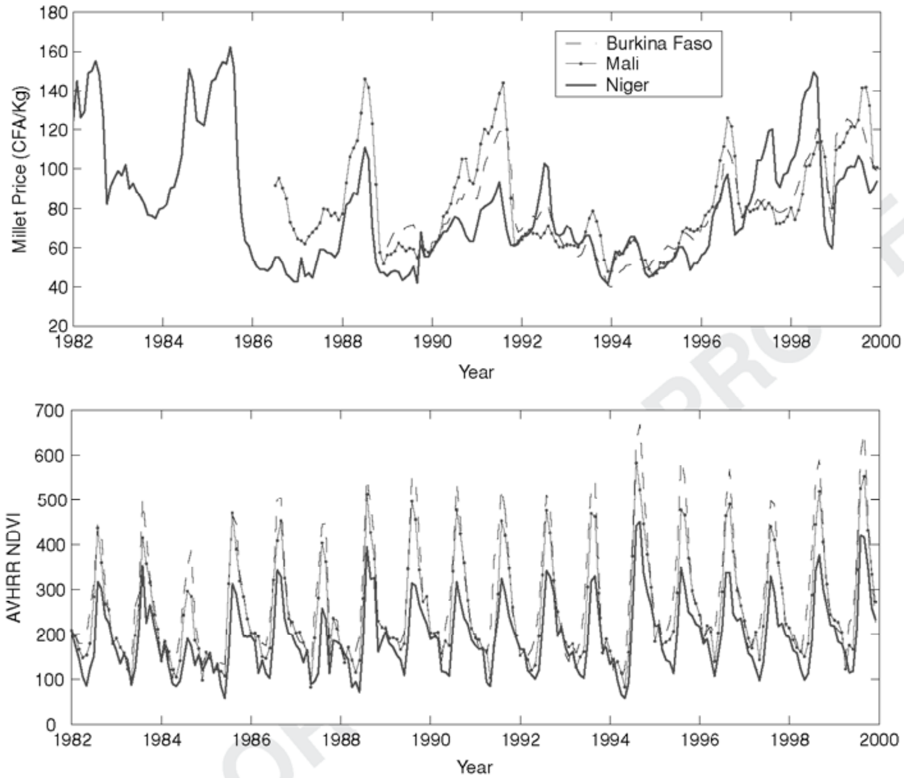


Figure 2. Upper panel: Averaged millet prices from Niger (117 markets), Mali (244 markets) and Burkina Faso (84 markets). *Lower Panel*: NDVI averages from all markets in the three countries. Note the strong seasonal cycle of NDVI, which responds to the growing season (July-September).

4. Results

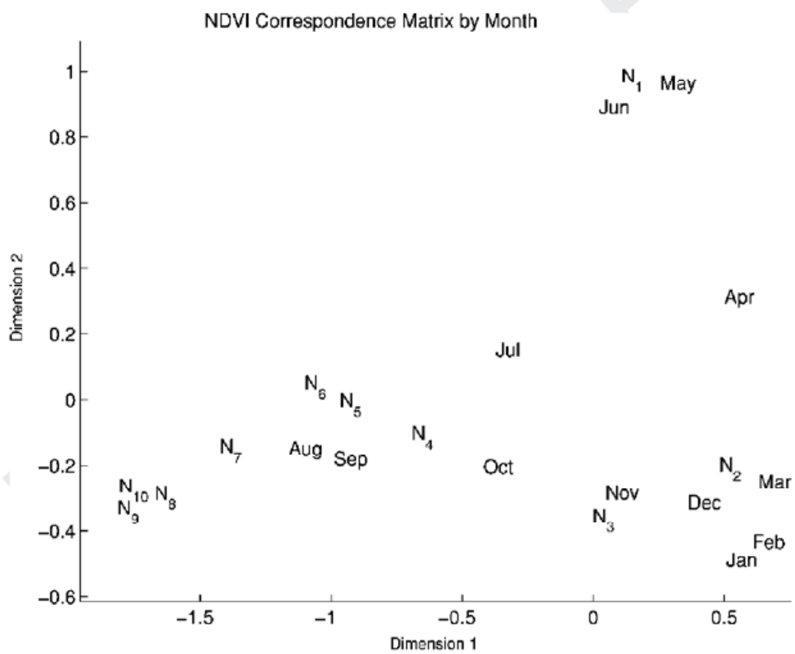
4.1. CORRESPONDENCE ANALYSIS RESULTS

Sahelian NDVI peaks during July, August and September, as indicated by the correspondence analysis where August and September are placed close to the highest NDVI values, N_7–N_{10}. Low NDVI levels of N_1–N_3 are associated with the dry season, from November-June when vegetation is scarce. May and June have the lowest NDVI not only due to the lack of vegetation production but also due to an increase in atmospheric water vapor during this month, which absorbs more near infrared radiation, depressing the NDVI still further (Los et al., 1994).

Figure 3b shows that millet prices also have a strong seasonality. The lowest price (P_1) was placed close to November and December in the correspondence analysis (Figure 3b), when millet is harvested and is most available in the Sahel.

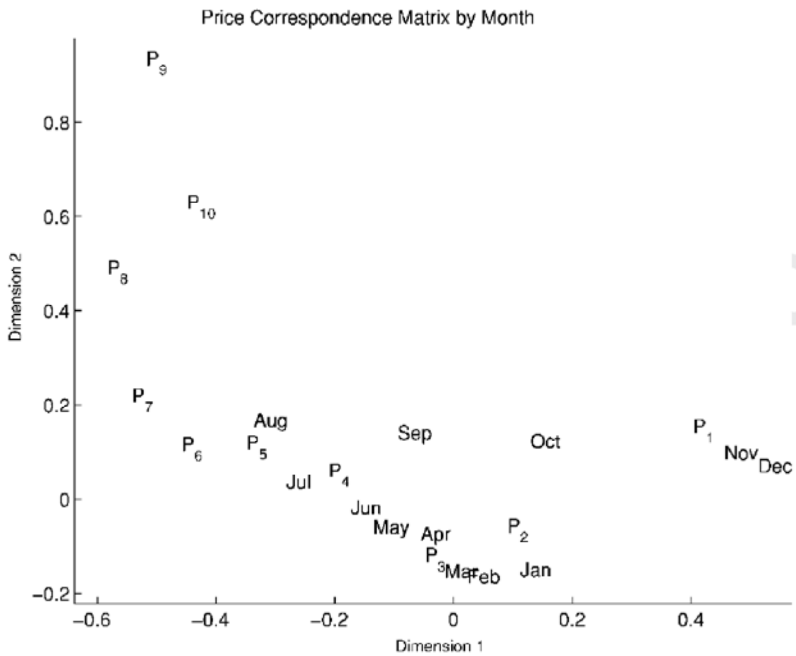
The analysis also showed that prices increased from January, when the price is in the range of P_2, to June when the price has reached P_4. The higher prices (P_4 and P_5) were associated with the months just prior to the harvest, July and August. The highest prices (P_6–P_{10}) are not associated with any particular month, indicating that they occurred at all times during the year, but were most closely associated with the pre-harvest summer months, known locally as the 'hungry season' or 'Soudure' (Toulmin, 1986; Glantz, 1990; Cekan, 1992)). The sharp increase in prices around August was associated with declines in available supply, along with many other factors that influence prices, such as increased demands on time and money, influence of food aid, and the livestock market.

The correspondence plot of price and months suggests that seasonality may influence the detection of interannual variation in prices. The seasonality of price



(a)

Figure 3. (a). NDVI correspondence matrix by month. Scatter plot of the first (Dimension 1) and second (Dimension 2) components of the singular value decomposition of a matrix created by counting the number of times during each month the NDVI from the 445 market locations fell into the ten ranges (N_1–N_{10}) of NDVI * 1000 units, ranging from a minimum of 50 to a maximum of 550 NDVI units at intervals of 50. The first component explains 39% of the variance and the second 71%. (b). Millet Price correspondence matrix by month. This scatter plot of the first (Dimension 1) and second (Dimension 2) component of the singular value decomposition of a matrix, created by counting the number of times during each month the Price from the 445 market locations fell into the ten groups (P_1–P_{10}) of 22 CFA each, ranging from a minimum of 3 to a maximum of 225 CFA/kg. The first component explains 50% of the variance and the second 75%. *(Continued on next page)*



(b)

Figure 3. (*Continued*)

must be taken into account if the influence of the variations in vegetation production from year to year are to be detected. Prices were therefore grouped into three periods: harvest August-December; post-harvest July-April; and transition May-July. Millet prices and the NDVI had a weak negative relationship, so that a negative anomaly was associated with a higher than average price (Figure 4). Table II shows the average price for the three countries in average, below and above average NDVI years. The correspondence plot (Figure 5) of the price, divided into five levels (P_1lowest, P_5 highest) vs five levels of NDVI anomaly of the August-September mean also shows the correspondence of the two variables (Figure 5). High price levels (P4 and P5) are placed close to bad agricultural seasons, represented by production that is very low with respect to the 18 year mean (Very Neg), meaning that prices were high when production was low. In addition, low prices (P_1) were very closely associated with above average vegetation and production (Very Pos).

4.2. IMPROVING PREDICTIONS USING NDVI ANOMALIES

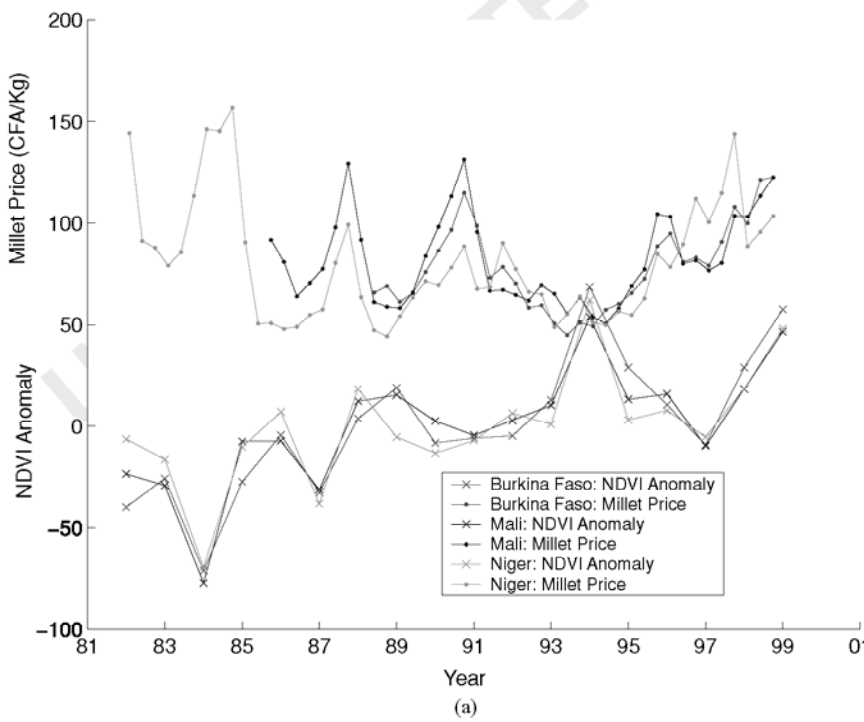
4.2.1. *Overview of Markov Matrices*

The Markov properties of the millet price data were explored by using the entire price dataset to produce a single transition probability table (Table IV). This was

TABLE II
Millet Prices (CFA) in the August-September period (maximum vegetation production) averaged by country and by NDVI anomaly

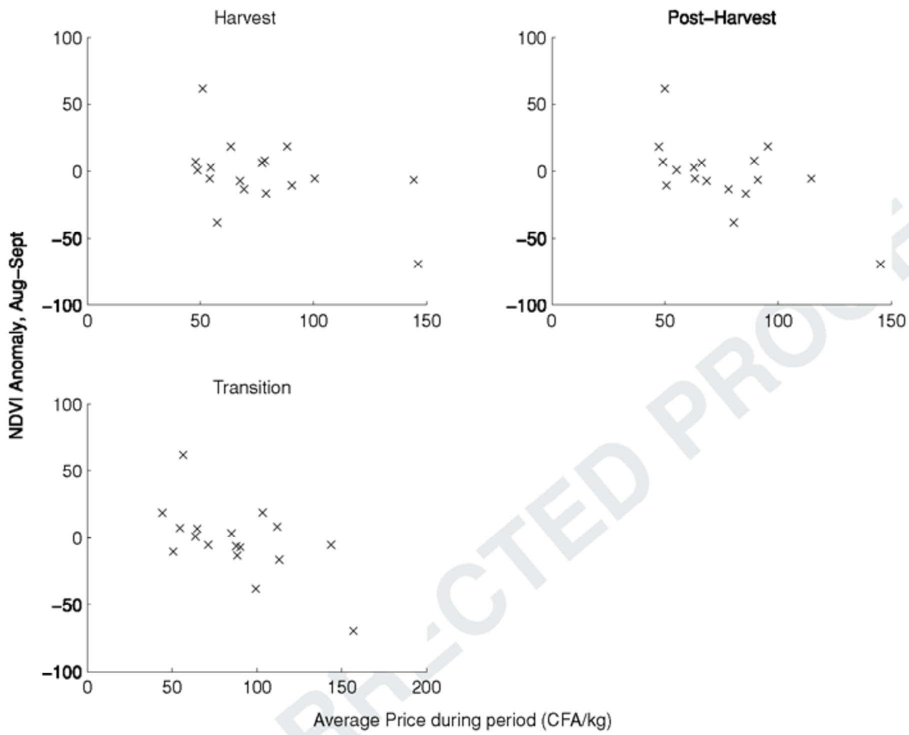
NDVI anomaly range	Burkina Faso	Mali	Niger
Above average	81.81	54.10	52.46
Normal	75.11	81.97	78.64
Below average	no data	101.46	114.63

done by determining the probability of the transition of prices from one price group of 22 CFA/Kg (i) to another (j). The χ^2 probability was very much less than one in ten thousand ($p << 0.0001$) (Freund and Simon, 1995) and hence the null hypothesis that the tables could be the result of random variation can be rejected



(a)

Figure 4. (a). Millet prices and NDVI anomaly averaged during three periods: Harvest (August-December); Post-Harvest (January-April); and Transition (May-August). Data averaged by country and plotted three periods per year. (b). Millet prices (x axis) from Niger plotted against August-September NDVI anomaly (y axis) by year. The three panels shows the Harvest, Post-Harvest and Transition period averaged vs NDVI anomaly. *(Continued on next page)*



(b)

Figure 4. *(Continued)*

(Anderson and Goodman, 1957). The single probability table had a strong diagonal structure (Table III). The prices tended to be concentrated around price levels 1, 2 and 3, with declining probabilities as the price increases. The converged matrix (Table IV) shows the stable behavior of the matrix. The peak probabilities were in price ranges 2 (25–47 CFA/kg) and 3 (47–69 CFA/Kg). The probabilities fell off after the third level since higher prices are uncommon.

The price prediction for a market in Niger using the single Markov probability table (Table III) is shown in Figure 6. The Markov probability table was able to capture the variations of the price in the market from period to period. Because only in large variations of prices are of interest, the quantized predictions are sufficiently accurate to capture the overall changes in price.

4.2.2. *Comparing the Markov Matrices From Different Years and Different Seasons*

By comparing the single probability table described above to those for different seasons and years, the influence of the varying vegetation production on millet

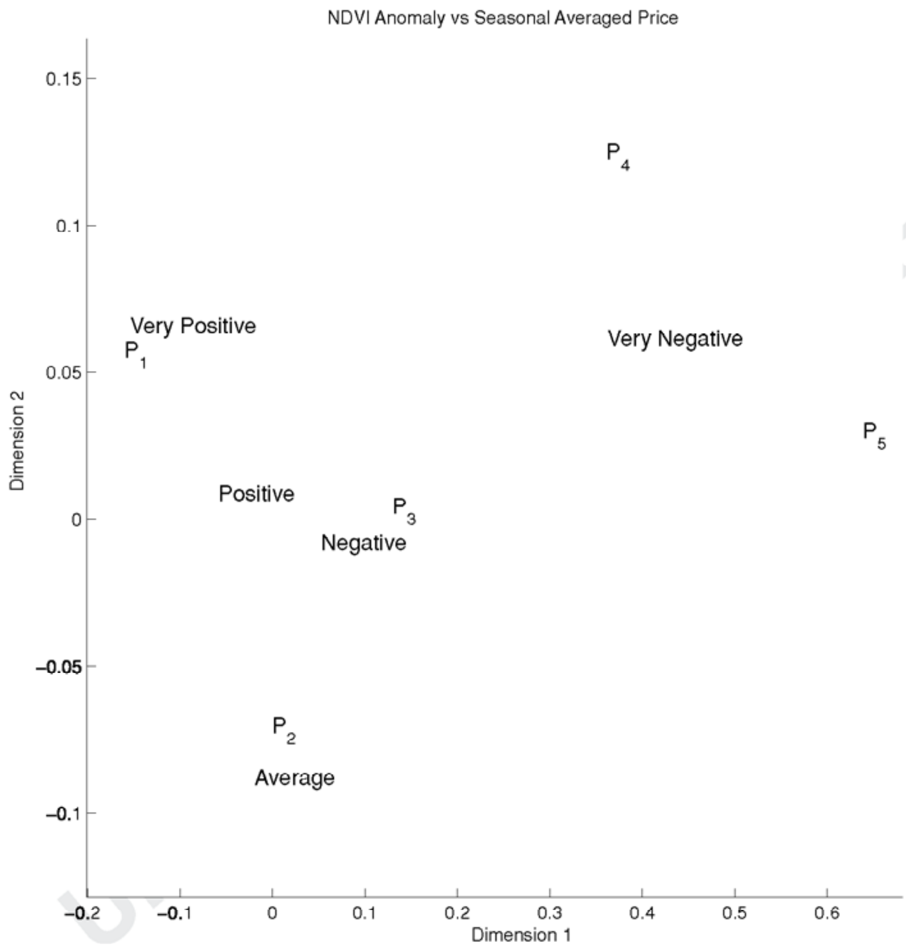


Figure 5. NDVI Anomaly vs Seasonal Averaged Price correspondence plot. The scatter plot of the first (Dimension 1) and second (Dimension 2) component of the singular value decomposition of a matrix created by counting the number of times the price was in one of five groups of 44 CFA/kg (from 3 to 225 CFA/kg) during years with a very high negative anomaly (less than –20 NDVI units), high negative anomaly (−20 to –10 NDVI units), average anomaly (−10 to 10 NDVI units), high positive anomaly (10 to 20 NDVI units) and very high positive anomaly (greater than 20 NDVI units). The figure shows the correspondence between the high prices and the poor growing seasons (negative NDVI anomaly) and the low prices and the good growing seasons (positive NDVI anomaly). The first dimension accounted for 66.5% of the variance and the second 92% of the variance.

prices can be seen. Probability tables were constructed from the price data using vegetation production information (above, normal or below average) or on time of year (harvest, post-harvest and transition). These tables were used to determine the effect of varying production or time of year has on the price of millet.

TABLE III

A. Markov transition probability table for all years, all markets and all countries. Numbers represent levels of prices in groups of 22 CFA/kg (level 1 is from 3 to 25 CFA/kg millet, 2 for 26 CFA/kg millet . . .)

i/j	1	2	3	4	5	6	7	8	9	10
1	**0.77**	*0.22*	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.09	**0.76**	*0.14*	0.01	0.00	0.00	0.00	0.00	0.00	0.00
3	0.01	*0.13*	**0.71**	*0.13*	0.01	0.00	0.00	0.00	0.00	0.00
4	0.01	0.03	*0.18*	**0.59**	0.17	0.02	0.00	0.00	0.00	0.00
5	0.00	0.02	0.07	*0.20*	**0.61**	0.09	0.01	0.00	0.00	0.00
6	0.00	0.02	0.05	0.08	*0.24*	**0.46**	0.13	0.01	0.01	0.00
7	0.00	0.02	0.06	0.07	*0.14*	**0.28**	**0.39**	0.04	0.00	0.00
8	0.00	0.00	0.06	0.00	*0.17*	**0.39**	*0.22*	*0.17*	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	**0.50**	0.00	**0.50**	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

TABLE IV

Converged Markov transition probability table of the Markov probability matrix given in Table III, rounded to two decimal places, created by multiplying Table III by itself 100 times

p_o	0.14	0.30	0.27	0.15	0.10	0.03	0.01	0.00	0.00

The transition probability tables from the millet price data produced for the three periods of the year were quite different from the single annual matrix. By separating the prices into three periods: post-Harvest (January–April), transition (May–July), harvest (August–December) (Figure 7a). Differences in the Markov properties of the matrices emerged during the three periods, thus demonstrating the appropriateness of separating the price periods in this way.

Figure 7b shows the converged probabilities of the seasonally averaged data, where three probability matrices were developed using the NDVI anomaly. The vegetation production anomaly of the August-September period was used to determine the quality of the growing season for the following year. Comparing the probability of the positive production years to the neutral production years and the single matrix with all years, there was a significant difference in probability of having prices in level 3 and 5. This means that in years with positive vegetation production anomalies, prices have a more even distribution across all levels. The negative anomaly years, however, tend to have a larger proportion of the price ranges peak higher than when all years are considered.

A possible application of the grouping of millet prices into three periods is to be able to estimate the seasonal price increases that occur during the transition period (May–July) after the harvest has occurred in December. Once the prices

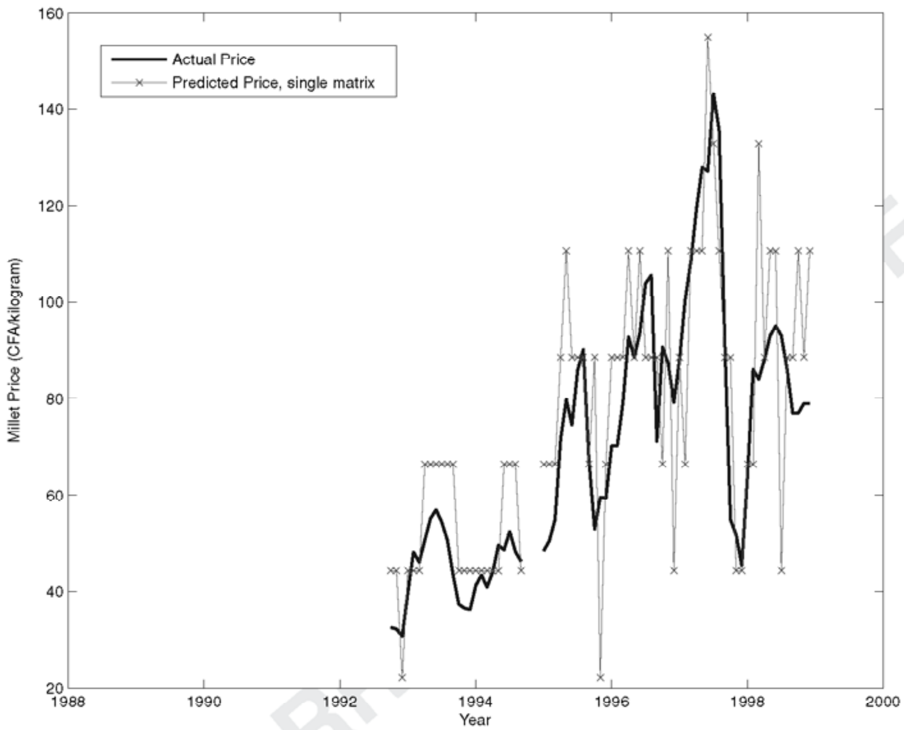


Figure 6. Millet price time series from Matameye, Niger and the estimated series using a single Markov probability table created from the entire dataset. First price is taken from the time series, the rest estimated using the probability matrix.

were established in the post-harvest period (January–April), the transition prices in June–August could be estimated directly (Figure 8). A less direct relationship was seen between the transition and the harvest periods and the harvest and post-harvest periods.

4.2.3. *Improving Price Estimation Using Markov Matrices*

Table V shows the improvement in RMSE when taking the vegetation production into account and when using only one probability matrix for all years and when using three probability matrices for above, below and average production anomaly years. By taking into account the vegetation production information, an improvement on the price prediction was found. Although small, the improvement was consistent when predicting prices 1 month, 4 months and 12 months in advance. This result motivates continuing research using Markov matrices to develop a model that takes into account the seasonal and interannual variation while maintaining the single Markov chain using conditional probability.

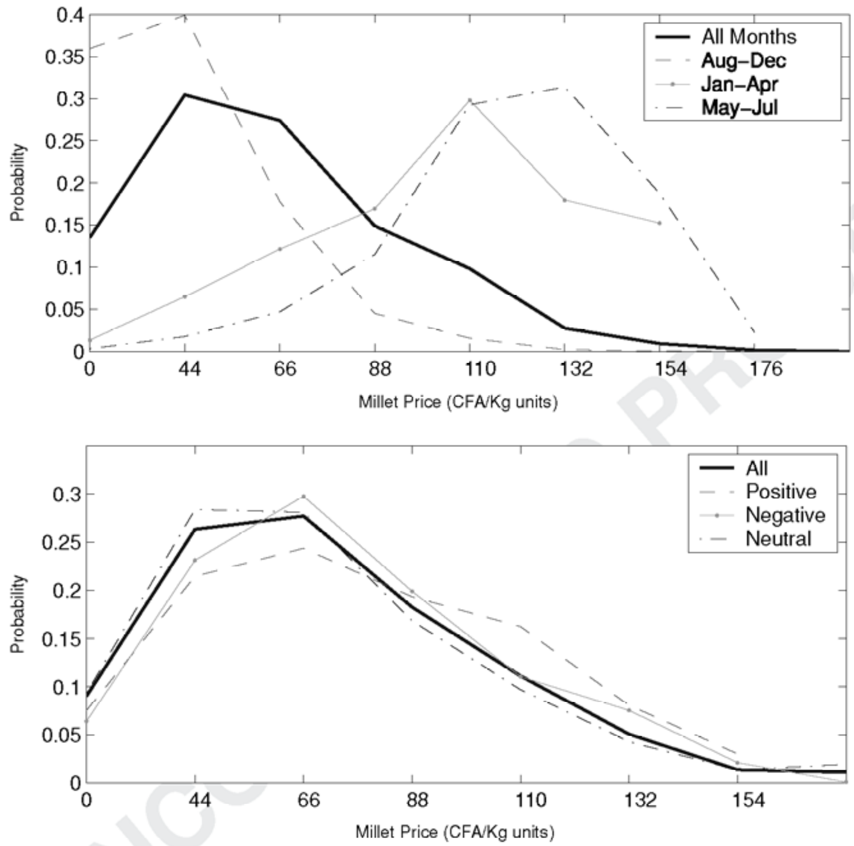


Figure 7. Millet price modeled by converged Markov matrices for markets in Mali, Niger and Burkina Faso. (a). Converged matrices from the Harvest (August-December), Post-Harvest (January-April), and Transition (May-July). The dark line is the converged matrix from all months. (b). Converged matrices from price data during years with a positive NDVI anomaly (above 20 NDVI units), negative anomaly (below −20 NDVI units) and neutral anomaly (between 20 and –20 NDVI units). The dark line is the converged matrix from all months.

4.3. CREATING MAPS OF INCREASED FOOD INSECURITY

Maps can be made of West Africa showing the contribution of the vegetation production to price dynamics in both space and time (Figure 9). Areas with yellow or red were regions that had a poor growing season and thus a high price for millet, given previous price behavior in the region. By translating the NDVI anomaly into price variations, the impact of the vegetation production is made explicit. The maps of correspondence are extended to areas outside the three countries used to provide data for model calibration because we expect to see similar variations in food prices in the entire region. This is reasonable because of the relatively open borders

TABLE V

Error of prediction from model using Markov matrices developed on averaged data. The prices are predicted 12 months, 4 months and 1 month in advance and the root mean square error calculated from the actual prices

	Root mean square error	
Months in advance	Single	NDVI Anomaly
12	42	40
4	33	32
1	32	29

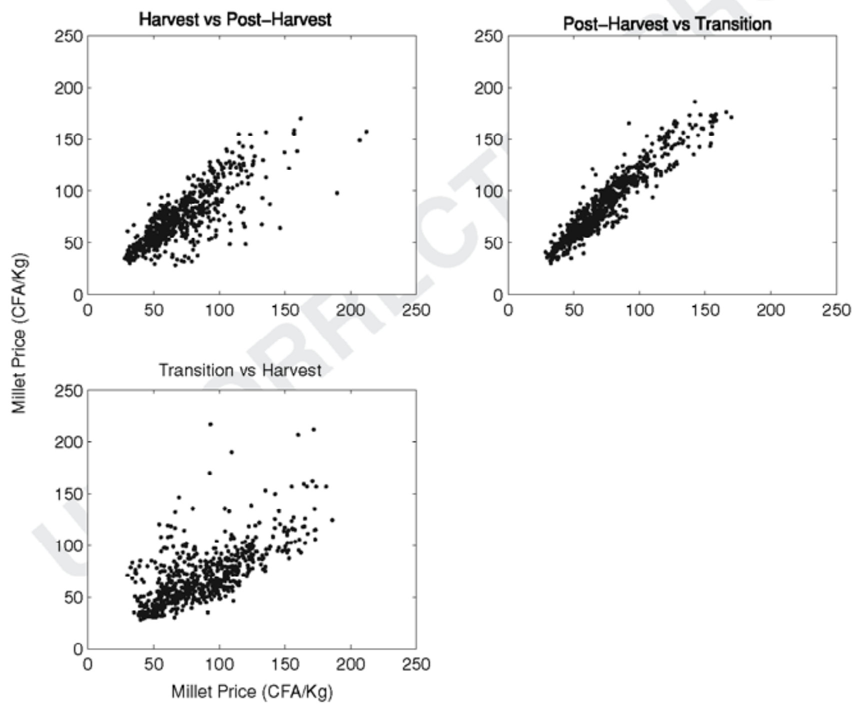


Figure 8. Scatterplot of price data from Niger, averaged during the harvest, post-harvest and transition periods, showing the relationship between the prices averaged over each period. Panel labels: first label is x axis price, second label is y axis price. Units are CFA/kilogram.

between countries, the extensive food trade seen in this region, and the participation in the CFA currency zone by Senegal and Chad (Lofchie, 1987; Meagher et al., 1996; Yade et al., 1999). In addition, by extending the price data regime through the entire region, we can in future work validate the maps and analysis with price datasets from these other countries.

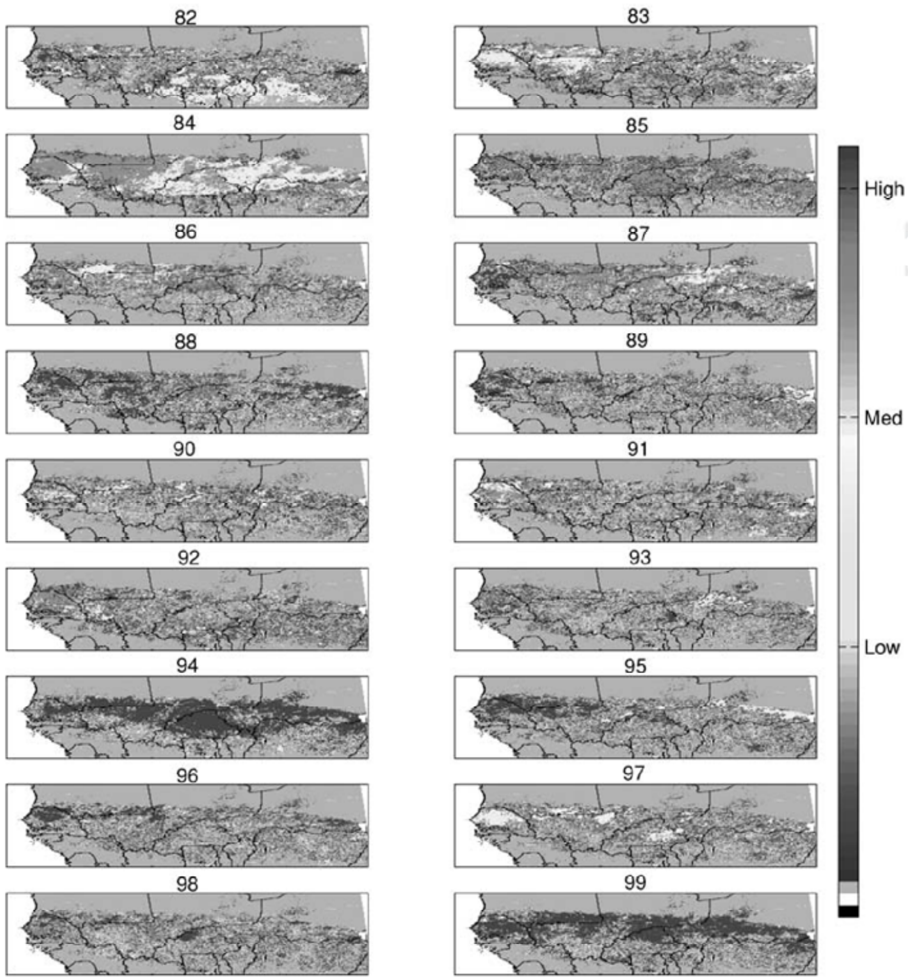


Figure 9. Yearly NDVI anomaly images transformed into food insecurity indices using correspondence analysis results presented in Figure 5. Colors on map indicate levels of insecurity shown by the color bar: red (High insecurity), yellow and orange (Medium insecurity). Strong positive and neutral vegetation anomaly have a lesser effect on prices and are indicated by green and blue colors (Low insecurity).

5. Discussion

The research presented addresses an important and long-standing issue of how to measure human vulnerability to changing economic and vegetation conditions through time over large areas in West Africa. The complexity of vulnerability and the diversity of social systems make early warning of food insecurity difficult.

Food prices are influenced by a diversity of factors, including social unrest, macroeconomic policies of the governments, food and income assistance often from multiple sources, regional price and crop production variations, and demand and other market factors (Singh, 1988; Delgado and Jammeh, 1991; Jaeger, 1992; Reardon, 1993; Tomek and Myers, 1993; Deaton and Miller, 1996; Grabowski and Shields, 1996; Fafchamps and Gavian, 1997; Dieng, 1998). By focusing on two measurable variables that have meaning in much of the region, prices and NDVI, and connecting them to each other in a realistic model, the available vulnerability indicators can be improved.

When food prices are high and production low, households that practice subsistence farming are forced to use a variety of strategies to survive until the next crop production season (Corbett, 1988). This involves purchasing food grains in nearby markets with whatever income is available. Farmers who switch between selling food after the harvest and purchasing food during the growing season are disadvantaged due to the price distributions that follow naturally from food marketing patterns in infrastructure-poor economies (Barrett, 1996). The price of food grains is an important indicator of access to food as well as a determinant of welfare.

Approximately 85% of the cereal energy consumed by rural households in semiarid West Africa is from maize, millet and sorghum, with imported Asian rice providing the remaining 15% (Jayne and Minot, 1989; Jayne et al., 1994). In Niger, millet contributes about 75% of national cereal production and is the main staple food (Amadou et al., 1999). With the exception of highly urban or monitized communities that rely on cash crops or have substantial off-farm income, reliance on locally grown millet and sorghum is nearly universal in the rural areas of the Sahel (Reardon, 1993). Households in the Sahel both sell own-produced grain and purchase grain on a yearly basis. Grains purchased by rural households in Burkina Faso's local markets increased from 30 to 40% of the caloric intake to over 50% during the hungry season when locally-held stores were exhausted (Reardon, 1990). A survey conducted in Mali of 190 farm households revealed that 39% were net buyers of cereals, 48% were net sellers, and only 13% had no net sales or purchases (Dione and Staatz, 1987). This survey was carried out in the major grain production zones of Mali in a good year, so the numbers are likely to be conservative. The implication is that the rural population is heterogeneous and that higher grain prices can have a negative effect on the portion of rural households that are net purchasers of grain, especially those who are forced to rely on the markets during the hungry season.

Food price sector instability is closely related to transitory food insecurity, because the normal levels of availability of and access to food are so low. Variation in rainfall is the main cause of production instability (Kangasniemi et al., 1993). African food markets are also affected by erratic sales of accidental food surpluses, resulting in very thin markets that are insufficiently integrated to withstand the resulting wide variations in production (Staatz et al., 1989). The resulting co-incidence of high food prices during periods of low production (below normal NDVI) and low prices during periods of high production (above normal NDVI) result in severe reductions in people's real (subsistence of cash) incomes and access to food, resulting in food insecurity. The NDVI anomaly can therefore be used to indicate areas where food price and food production instability coincide.

Although annual crops such as millet showed a high degree of correspondence to NDVI anomalies, the price of other rainfed crops such as cotton seem to be more correlated to the international price (Deaton and Laroque, 1992; Bruentrup, 1996). Because millet is a low-value crop, and the transportation and transaction costs in West Africa are so high, it is not exported or imported into the region (Goetz, 1992) and is thus only minimally influenced by international markets (Kangasniemi et al., 1993). Thus, millet can be seen as an indicator of the overall availability of food in the region.

Transforming spatially explicit databases such as NDVI into tools for both understanding of the pattern and cause of variation of prices will create new ways for decision makers to improve food security. This approach permits the determination of food prices in places where no historical price data are available, by using the concept of a 'virtual market', or the millet price that a market would have had, assuming it were to behave similarly to the nearest actual market. Information regarding the overall price and the spatial extent of similar prices can be estimated using the research presented here. The ability to have knowledge about very local market conditions is a significant improvement over point market data. It permits the determination of food prices at places where no historical price data is available, and provides information as to where the price changes from one level to another on the landscape. This information could provide a basis for policy advice to local, regional and national organizations and individuals concerned with food marketing and food security.

The next step in this research is to develop decision support tools based upon the work presented here. Even taking the single matrix shown in Table II a and modifying it by the differing effects of the time of year (harvest, post-harvest and transition) and by the NDVI anomaly (above, below or average) for that year improved our prediction of the dynamics of millet prices. Integrating the probability matrices into the spatial representation of the intersection of price and NDVI, as was shown in Figure 9, is also an essential next step in this research. We showed how vegetation production could be taken into account both spatially and temporally to improve predictions, not just as a static variable as in earlier studies (Deaton and Laroque, 1996; Deaton and Miller, 1996).

6. Conclusion

Agriculturalists in West Africa use multiple strategies to reduce consumption risk in a semi-arid region where food production may vary greatly from one year to the next, and attempt to reduce exposure to seasonal price increases through storing and consuming the grain they produce themselves. These adaptive behaviors have been successful in sustaining agriculture in a highly variable, semi-arid environment for centuries. Given the potential for a reduction in overall rainfall and an increase in year-to-year rainfall variability due to climate change, coupled with historically high and increasing population and a static natural resource base, new strategies and development policies may be needed to successfully adapt to changes in the climate.

Spatially explicit information on how locally-grown food production and food prices are related, and maps of this interaction, can provide essential information to organizations or governments that focus on agriculturalists who may be isolated, marginalized or otherwise unaware of market forces regionally. Farmers who are the most vulnerable to declines in food production and food price increases are also those with the fewest resources to respond to prevailing market conditions. By targeting these vulnerable segments of society with aid, information and assistance, market functioning might be improved while simultaneously improving food security. Although many forces affect food prices beyond supply, the interaction of prices and vegetation productivity are basic and a better understanding of these might enable vulnerable populations to cope with climate change.

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